Generalizable occupant-driven optimization model for domestic hot water production in NZEB

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Highlights

- Domestic hot water (DHW) consumption and smart meter data for its provision is collected for 40 residential NZEB in the Netherlands
- A separate control group of 6 houses is used for testing purposes
- An offline, generalizable model is built for the storage vessel which is calibrated dynamically once in operation; models for occupant behaviour and heat pump are learned online
- Simulation results show 20 - 27% expected savings in electricity energy consumption for DHW production; the energy savings for a house depend primarily on occupant behaviour
- Active control implemented on a Dutch NZEB for 3.5 months resulted in energy savings of 27% (61 kWh in absolute terms)

Abstract

The primary objective of this paper is to demonstrate improved energy efficiency for domestic hot water (DHW) production in residential buildings. This is done by deriving data-driven optimal heating schedules (used interchangeably with policies) automatically. The optimization leverages actively learnt occupant behaviour and models for thermodynamics of the storage vessel to operate the heating mechanism – an air-source heat pump (ASHP) in this case – at the highest possible efficiency. The proposed algorithm, while tested on an ASHP, is essentially decoupled from the heating mechanism making it sufficiently robust to generalize to other types of heating mechanisms as well. Simulation results for this optimization based on data from 46 Net-Zero Energy Buildings (NZEB) in the Netherlands are presented. These show a reduction of energy consumption for DHW by 20% using a computationally inexpensive heuristic approach, and 27% when using a more intensive hybrid ant colony optimization based method. The energy savings are strongly dependent on occupant comfort. This is demonstrated in real world settings for a low-consumption house where active control was performed using heuristics for 3.5 months and resulted in energy savings of 27% (61 kWh). It is straightforward to extend the same models to perform automatic demand side management (ADSM) by treating the DHW vessel as a flexibility bearing device.

Keywords

Domestic hot water (DHW), reinforcement learning, optimal control, occupant behavior, NZEB, heat pumps

1. Introduction

1.1 Relationship with existing literature

Anthropogenic climate change is one of the greatest challenges facing humanity in the 21st century [1]. Much of this is a result of burning fossil fuels to power civilization. The built environment alone accounts for about 40% of the overall energy consumed in the EU [2]. Widespread scientific evidence for the adverse effects of fossil fuels has, at least in part, led to substantial mitigation efforts: manifesting in the development of widely adopted energy efficiency measures and distributed renewable generation [3].

According to the main EU policy for buildings in the Energy Performance of Building Directive (EPBD) first introduced in 2002 [4] and then recast in 2010 (Directive 2010/31/EU [5]), each member state is mandated to have energy efficiency measures in place for all new buildings to consume nearly zero energy by 2020. Such measures consist of minimum requirements for heating and cooling systems, building opaque envelopes and façades, as well as the integration of RES and domestic hot water (DHW) production [5].

In the Netherlands, a compulsory performance certification for all dwellings was introduced in 2008, based on dwelling physical characteristics and energy needs for heating, cooling, and ventilation. However, there was no significant decrease in either gas or electricity consumption at the household level between 2008 and 2010 [6]. Despite mandatory energy-efficiency measures, a study conducted by [7] comparing labelled theoretical energy use of around 200,000 dwellings in the Netherlands with actual energy use data showed diverging behaviour. In low-efficiency dwellings, they found the theoretical consumption to be higher than actual consumption while high performing dwellings (energy label A-B), consumed much more than predicted. Further research reinforces the notion that if occupants don't operate in an efficient way, i.e. one that supports design intent, high-performance standards can be compromised [8]. Without considering occupants' support of a building's high-performance attributes, even well-designed buildings can fail to measure up to their high-performance potential. This means that, in nZEB, efficient (or otherwise) operation of the energy systems has become a key determinant of the global energy performance (EP). Building occupant behaviour is then the most susceptible part of the energy system.

This is not a recent phenomenon. A number of studies over the last decade have highlighted the extent of variability that exists in terms of operation and management settings in buildings, where the "human factor" is central to energy consumption levels [9, 10]. Bordass et al. [11] have alluded to this "loss of credibility" when design expectations of energy efficiency and actual building consumption differ substantially. These gaps arise primarily because the design assumptions related to the day-to-day use of building systems and technologies are not informed well enough by what really happens in practice [11].

In this context, the IEA EBC Annex 66 – "Definition and Simulation of Occupant Behaviour in Buildings" Project [12] aims to catalyse international efforts towards the standardization of quantitative description of the impact of occupant behaviour at the building level. In order to investigate the extent of this 'human factor' on final energy performance, recent years have seen many advances in the integration of more accurate behavioural variables - such as interaction with control systems, presence, and movements - in building energy models. Different methods to develop behavioural models were classified by the IEA Annex 53 [13]. This methodological approach relies on stochastic behavioural models built upon the statistical analysis of real occupant interaction within the building controls.

In the context of energy consumption in residential buildings, domestic hot water (DHW) is often the second largest single draw on energy consumption after HVAC [14] and, in many cases, can account for as much as 10% of the end energy use [15]. It is projected to become even more important in relative terms as improved façade technologies dramatically reduce cooling and heating loads in nZEB. There are two broad, but not mutually exclusive, ways to reduce the energy load for DHW: (1) by improving the efficiency of the heating mechanism, and (2) by utilizing information about occupant behaviour to reduce unnecessary and inefficient heating cycles. Much work has been done on the former, with higher efficiency boilers, heat pumps and solar water heaters now widely available [16, 17]. Of these, solar heaters have to compete for limited installation space in residential buildings with solar PV panels and the choice between the two, while financially motivated, is still rather arbitrary. At the same time, proliferation of air source heat pumps has accelerated; these offer generally higher thermodynamic performance with an efficiency that depends on a number of different factors and is thus time-variant.

Occupant behaviour, on the other hand, has arguably an even greater impact on the energy consumed for DHW provision. In light of this, quantifying and modelling occupant behaviour as it relates to energy consumption due to DHW will only increase in importance as a necessary first step in an attempt to reduce this load. The gains in energy efficiency achieved by improved heating technologies have highlighted the influence of occupant behaviour on residual demand (e.g. DHW) in the context of high performing buildings [18, 19] and net zero energy neighbourhoods [20].

While there have been steady improvements from the thermodynamics perspective, incorporating occupant behaviour into DHW heating schedules has lagged behind. It is well known that control strategies significantly influence the DHW supply and the tank performance [21]; the development of a robust DHW model hinges on the storage vessel tap profile and the total hot water consumption. Both of these aspects are strongly related to the activity of the building users. Several stochastic models for the DHW storage vessel profile can be found in literature, based on the approaches of [22, 23] with De Coninck et al. [20] providing a comprehensive review.

Several experimental studies have been conducted and published in recent literature, testing the DHW storage tank efficiency, under varying operating conditions. In some of these studies [24, 25], DHW inlet water temperature has been considered mainly constant, in other cases [26, 27] it varied based on charging and discharging periods. Still, limited literature exist, correlating the thermal performance and efficiency of storage tanks and DHW system operation in real case studies [28] and building energy simulations [29, 30, 31, 32]. This is partially attributable to a limited understanding and knowledge of actual occupant behavioural patterns and activity schedules in the residential domain [33]. This inconsistency is exacerbated by a lack of experimental data concerning the thermal performance of storage tanks, under real world operating conditions. Hence, models of more realistic operation conditions must be scrutinized and employed when designing, operating and retrofitting DHW production systems in residential buildings.

So far, simulation studies are usually implementing simplified DHW load profile (e.g. according to prEN 12977). Assumptions about the distribution of the DHW consumption during the year, depending also on the day of week and time of day are typically adopted. However, more realistic profiles need to be generated. To study the influence of the draw-off duration and flow rate as well as the daytime of DHW consumption, Jordan and Vajen [30] carried out TRNSYS simulations, by employing realistic DHW-load profiles. By doing so, results confirmed a 2% energy savings for the DHW system operation. More recently, Spur et al [31] developed and validated a TRNSYS simulation model, virtualizing the thermal behaviour of a DHW storage system. This model simulates the dynamic heat-reduction and recovery processes of the DHW system and predicts the transient temperature-patterns for various DHW draw-off versus time profiles. Realistic daily profiles based on field studies were developed representing draw-off patterns for the testing of thermal stores and simulation studies. Simulation results point out the importance of the number, type and time of occurrence of the DHW draw-offs on the thermal store's performance. Moreover, it concluded that more realistic DHW usage profiles should be used in the performance testing of thermal stores to obtain results that reflect conditions experienced in the field. A simulation model developed by Moreau [32] takes into account the diversity of the population's hot water withdrawal profile. This model was based on time-use data of 8,167 real water withdrawal profiles of several clients under different operating conditions.

There is a need for a method that accurately assesses the user-related effectiveness and optimized control logic to enhance the energy efficiency of contemporary DHW system. Mathematical models have been developed and validated using measurements obtained from experiments, which required a realistic daily DHW draw-off for testing the DHW systems [34]. By adopting such modelling and simulation approaches, researchers [35] are identifying opportunities to improve the production efficiency of storage tank equipped DHW systems, through better control of heat inputs. In this context, Bøhm [36] acknowledged the efficiency of DHW distribution systems and by proposing data driven solutions for DHW system operation. Possibilities for improving the DHW have the potential of a 40% reduction of heat losses, not only in future buildings, but also in existing buildings when renovation of installations take place.

Nhut and Park [43] developed a study to determine optimal control variables to improve the performance of a DHW system. A mathematical model of the system is developed to predict its operating performance under real weather conditions. Results highlighted the DHW system performance is significantly influenced by operational variables such the change of initial water temperature and volume of the storage tank, as well as the collector area.

A model for computation DHW demand profiles from time-use data was developed by Widén et al [44] using water-tap data. Time-use data, describing in detail the everyday life of household members as high-resolved activity sequences, have been demonstrated having large potential to enhancing energy efficiency in domestic energy systems. More recently, Good et al [45] introduced and detailed a high resolution domestic multi-energy model including a physically based DHW model, investigating dwelling diversity. Additionally to previous studies, the importance of high granularity modelling is demonstrated.

These data driven approaches build on a number of classical algorithms for optimal control by planning in the future [37, 38]. Tackling DHW production optimally thus falls under a much broader taxonomy of constrained optimization problems. At the heart of many such approaches is constrained minimization of either the local energy consumption or some other cost function (e.g. shift consumption in time so as to offer flexibility for a balance responsible party (BRP)) while ensuring user comfort [39]. An example of incorporating occupant behaviour into such analysis is the use of moving averages of finite historical time series to serve as the forecast of consumption for realistic domestic hot-water profiles in different time scale for the next day [40]. More complex studies involve simulations relying on stochastic models and incorporate models developed using [41, 42]. Rule-based demand side management of domestic hot water production with heat pumps in zero energy neighbourhoods has also been investigated in the literature [20].

A unifying theme across much of this large body of existing work is first building a detailed thermodynamic model of the energy system and storage vessel, and then using this model to perform active control. This has poor generalization potential to real world deployment since, just as occupant behaviour is unique to each individual household, many more combinations of heating systems and storage vessels exist than can be reasonably modelled individually. Furthermore, as already mentioned, there is a large literature present which uses statistical averages of historic consumption profiles, with no active learning or adaptation in the real world.

1.2 Original contributions of the paper

The aim of this study is to improve the overall energy efficiency of existing NZEBs by deriving optimal control policies for DHW while remaining fundamentally agnostic of the physical or theoretical properties of the heating circuit itself. Approaching the problem in this way marks a departure from the established methodology of using detailed models for the DHW vessel and the heating mechanism. Furthermore, we assume no prior information about the occupant behaviour and develop models which learn these interactions on the fly as well. This marks the first step in a large scale research project which aims to optimize energy consumed for DHW provision in a completely automated manner. An additional

At the same time, the research project is grounded in reality, and this practical approach is demonstrated by running simulations using data from individual houses. Furthermore, the proposed algorithms are also implemented as part of active control in an NZEB, thereby investigating applicability in real world-settings.

Due to the wide variability in settings (heat pump and storage vessel types, occupant behaviour, operating conditions etc.) a hybrid reinforcement learning based approach [47] is adopted. Our approach shares some characteristics with the formulation of Batch reinforcement learning methods [46], however there are also several significant differences in which we approach the problem. Primarily, the learning in this context is carried out along two dimensions; first, the occupant behaviour and heating mechanism response is learnt on the fly. Second, optimal policies are also learnt from prior experience instead of using a more traditional algorithm like approximate dynamic programming. A key motivation to do this is the strong stochasticity and nonstationarity of occupant behaviour as well as nonlinearity of heating mechanism / storage vessel models. Doing so also allows us to circumvent the curse of dimensionality [48]. Finally, we compare the energy efficiency performance of actively learnt policies with the default control strategy as well as a computationally more tractable rule-based control strategy.

The novelty of the present work derives also from the fact that our key focus is to improve the energy efficiency of the DHW provision task itself by exploiting both the occupant behaviour and the device characteristics. This differs from a large body of existing literature where different formulations are used e.g. active demand response, mitigating transformer aging or maximization of local renewable generation. This does not preclude the use of models learnt in this research for any of these alternative formulations; indeed, performing active demand response can be carried out using this approach as well.

The paper is divided into three main sections: the methodology section describes the analysed systems and the algorithms used to model them; the results section explains main outcomes of the analysis while the discussion section highlights main innovation and benefits of the proposed work. The paper concludes with a discussion and an outlook to future research directions.

2. Methodology

This paper proposes a hybrid reinforcement learning for approximately optimal control in devising policies for DHW production. The objective function we minimize is energy efficiency. It is straightforward to extend the same methodology to optimize for a different objective function such as maximal consumption of local renewable generation, grid stability, dynamic electricity pricing, or any combination thereof.

2.1 System description and data gathering

The set-up consists of 46 homogeneous NZEB’s in the Utrecht province of the Netherlands. These houses form part of two separate electrified Net-Zero Energy Neighborhoods. The buildings have been recently refurbished with high-quality insulation to prevent transmission and infiltration thermal losses and each is equipped with its own air-source heat pump, DHW vessel and solar panel. The

capacity of the DHW vessel is 200 liters. The entire system is designed to ensure net annual energy neutrality.
Information from a number of sensors is utilized to perform active control. These include a hot water flow meter and a smart meter which records how much power is being consumed by the heat pump and the mode it is operating in (i.e. spatial heating, domestic hot water or idle etc.). Two temperature sensors are also made use of: an ambient temperature sensor and a sensor mounted mid-way in the DHW vessel, available by default. While the data is sampled uniformly in intervals of five minutes, depending on the task it is subsampled to varying degrees to make computation tractable. A rough schematic of the test setup is visualized in Fig. 1.

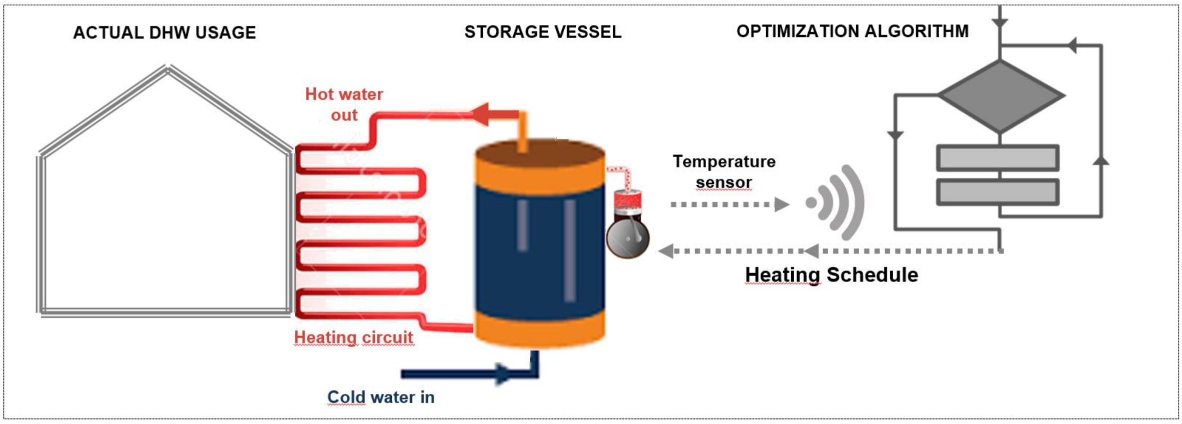

Figure 1. *Schematic for the experiment and control strategy for operating DHW storage vessel.*

2.2 Hybrid reinforcement based control strategy

In this section, we present the reinforcement learning for optimizing energy consumed by the heat pump to provide DHW while constrained on the user comfort. The adopted formulation of the problem is based on the standard tuple form used to describe a Markov Decision Process (MDP): *{x, u, f, c}* [23]. Here, x refers to the state of the storage vessel; u defines possible actions that the 'agent' (i.e. the heating mechanism) might take; f is the transition probability from a given state x_t to a new state x_{t+1} upon choosing action u_t and c is the cost incurred for executing this particular action. This is given as (Eq. 1):

$$x_{t+1} = f(x_t, u_t) + \varepsilon \tag{1}$$

The influence of environment, i.e. the occupant can either be included implicitly as stochasticity in the transition function or as an explicit interaction. We choose the latter approach and assume a completely deterministic system, thereby setting $\varepsilon = 0$. Future rewards are not discounted, i.e. $\gamma = 1$. In the following, we discuss the formulation of the 4-tuple in greater detail.

2.2.1. State, *x*

The state space of interest is the temperature distribution inside the storage vessel. However, as explained in section 2.1, only a single temperature sensor mounted mid-way in the vessel is available in the test setup. Accordingly, both thermodynamic (Section 2.3.1.1) and heuristics (Section 2.3.1.2) based models were explored to learn the behavior of the storage vessel.

2.2.1.1 Analytical solution

At each time instant, the temperature distribution inside the vessel is thermodynamically a function of (1) ambient heat loss, (2) occupant behavior (i.e. amount of water drawn) and (3) activation of the reheat cycle of the heat pump (Eq. 2):

$$\frac{dQ}{dt} = \dot{q}_{charge} - \dot{q}_{discharge} - \dot{q}_{loss} \tag{2}$$

Considering each reheat cycle as the termination of an 'episode', a charge cycle 'resets' the state of the storage vessel. This implies that the only realistic effects we are looking to model include heat loss to the ambient and by user consumption. Analytically solving the simplified heat loss model, and setting the charging term to zero, an estimation of the temperature can be obtained (Eq. 3):

$$T = \frac{\left(T_0 \dot{m} C_p + T_0 AU - T_a AU - T_c \dot{m} C_p\right) e^{\frac{-t(UA+\dot{m}C_p)}{MC_p}} + T_a AU + T_c \dot{m} C_p}{AU + \dot{m} C_p} \tag{3}$$

Here, the U-value of the vessel can be estimated based on repeated heat loss trials for any given storage vessel while the area is generally given in vessel specifications. The simplistic heat loss model described by (5) is problematic in practice: it doesn't account for fundamental spatial effects such as stratification [49]. This can be solved by developing either a layered thermodynamic model or a more elaborate CFD model. This approach is usually impractical in real life situations because of the large possible number of DHW vessel and heating mechanism combinations. This would necessitate new CFD models (or, at the least, recalibration of existing ones) for every new heat pump and vessel combination. Further, this approach is constrained by sensing limitations: precise mass flow information is not available because of coarse sampling of water consumption and the internal dynamics of the vessel are usually hidden or only partially observable. Both these drawbacks contribute to poor scalability in real world conditions.

2.2.1.2 Heuristic solution

To build a heuristic model for the storage vessel, the test setup was somewhat modified. Multiple tests were repeated using additional temperature sensors fit at different locations of the storage vessel. A nonlinear model was fit to the measurement information collected by the temperature sensors. The learning algorithm is in essence a nonlinear function approximation to observed system response of predetermined perturbations. Here, parameters that affect vessel state at any given time include the heat pump reheat strategy (i.e. the conditions which must be met for a reheat cycle to be initiated), the target temperature (i.e. the temperature to which the storage vessel is heated to) and user interaction with the storage vessel, etc. The nonlinear model parameters are then generalized using a bilinear interpolation function. This formulation allows extending this schema for modeling any heat pump and storage vessel combination after an initial offline step.

2.2.1.3 Model merging

To arrive at the best fit between different combinations of heuristic function fitting and the thermodynamic heat loss model, cross-validation was carried out to prevent overfitting. In the final model, which is a hybrid of the heuristic and the thermodynamic model, the temperature distribution is a 1-D vector, i.e. it is allowed to vary spatially along the y-axis but not the x- or z-axis. There are two possibilities to further improve the performance:

1. By increasing training data (i.e. training data gathered offline);
2. By combining the predicted and measured temperature using a Kalman filter framework [53].

The former is a straightforward data analysis problem since more offline data can be used to improve generalization using more complicated nonlinear models with stronger regularization. The latter allows correction for predicted vessel states in online settings by optimally combining information from the model's prediction of x and the actual measurement [50]. This allows us to form an a posteriori belief about the estimate of the temperature inside the storage vessel can be performed (Eq. 4):

$$\hat{x}_{t+1|t+1} = \hat{x}_{t|t} + K(E) \tag{4}$$

Where $\hat{x}_{t|t}$ is the a priori estimate, E is the residual error (i.e. the difference between the prediction and the observation) and K is the Kalman gain which modulates the sensitivity to error depending on the uncertainty. As an episode becomes more complex in its interactions with the occupant, an increasing uncertainty about the model's prediction is reflected in the Kalman gain K (Eq. 5).

$$K = \frac{R_P\, H^T}{HR_P H^T + R_M} \tag{5}$$

The measurement error covariance R_M arises from the quantization limiting the resolution of the sensor as well as turbulence and averaging effects affecting the sensor. The state from the observation can also only be sampled at discrete intervals, which limits its accuracy in high flow rate regimes. R_P represents the error covariance of the prediction and H is the transformation that maps the state to the measurement.

A complication arises in this model merging step because the true state to be estimated (i.e. the actual temperature distribution in the vessel) is only partially observable, i.e. can be sampled only at a certain point (via the mid-point sensor). This means that the observation is a scalar while the prediction is a distribution (i.e. a vector). Generalization from the observation to the distribution is performed by locally adjusting the temperature distribution in the direction the error was made. Fig. 2 summarizes this workflow:

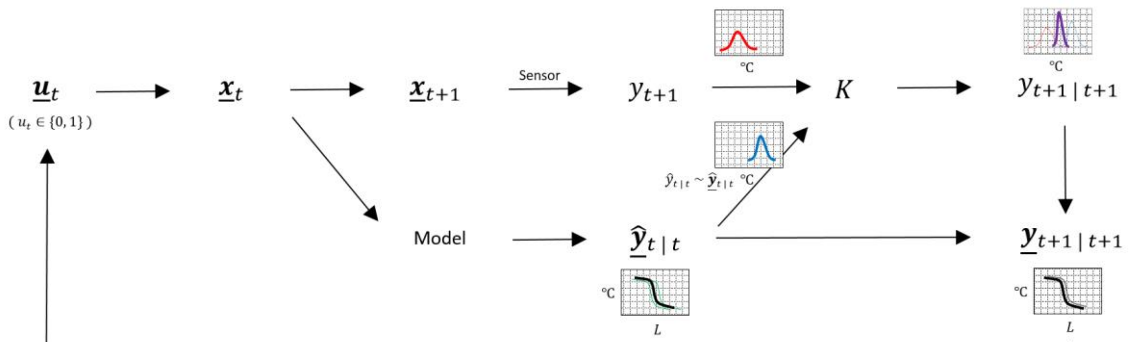

Figure 2: *Modeling the state of the storage vessel (bold-face variable names are vectors)*

This framework is intended to be entirely agnostic of different heating mechanisms and geometries. By learning system characteristics and then refining them during the operation phase, the model enables reliable estimation of the storage vessel state at any given time.

2.2.2. Action, u

The controllable action space is binary, i.e. $u \in \{0, 1\}$. Based on this control action, the heat pump can, at any given time, decide to either reheat the storage vessel or postpone the heating cycle. The purpose of performing active control is to find a policy, π, which minimizes the defined cost function.

2.2.3. Transition function, f

The transition function for the vessel state has been defined implicitly already in the Kalman fitler framework. Explicitly, for each different house the individual occupant behavior, i.e. consumption profiles, is also modelled. This then defines vessel state transitions. Occupant models are built explicitly and not subsumed as in a model-free approach. We feel this offers additional insight into individual occupant behavior types and can be used for subsequent machine learning tasks such as clustering of similar households etc.

Modelling occupant behavior is done using an ensemble of models. The ensemble includes predictions from a pool of SARIMA (Seasonal Auto-regressive Integrated Moving Average) models that fit historic data. Such models can identify and predict complex patterns in the data, however they break down in the face of highly irregular or random user behavior. The cost function minimized in these models penalizes over- and under-prediction of water consumption by a household equally. This is not true in this case: under-prediction needs to be penalized more heavily because it violates user comfort while over-prediction might lead to a slightly higher energy consumption. In practice, we do this by including an additional bias term in the form of a renewal process for houses on which the SARIMA prediction error is high.

2.2.4. Cost, c

This research is focused on minimizing energy consumption in houses for DHW provision without compromising user comfort. To maximize energy efficiency, we first developed a model describing how the heat pump consumes electricity (i.e. energy in kWh and not power). This energy demand was derived both analytically and heuristically. The analytic approach produced unacceptable results because it requires detailed knowledge about both the internal state of the storage vessel (i.e. inlet water temperature affects heat pump efficiency) and detailed coefficient of performance (COP) specifications for the heat pump under consideration. This information was not available; which further highlights the fact that, in practice, this approach has a lower probability of scaling to entire communities.

The immediate reward function, $c: (x_t, u_t, T)) \rightarrow e_t$ can be calculated for all x and T (the ambient temperature) using a model of the heating mechanism. In this case, the model is built using polynomial regression with regularization on multiple episodes of observed data (Eq. 6):

$$e_t = \begin{cases} f(x_t) & if\ u_t = 1 \\ 0 & if\ u_t = 0 \end{cases} \tag{6}$$

Extending this to a policy spanning an arbitrary time period, we get (Eq. 7):

$$J(\pi \mid x_0) = \frac{1}{T} \sum_0^{T-1} e_t \tag{7}$$

Lost user comfort is, as previously mentioned, valued higher than marginally higher energy consumption. We tackle this issue in section 2.4 where we discuss different control strategies.

2.3 Optimization algorithm

In this section, we introduce three types of control strategies, each bring additional increases in efficiency but also incurring successively greater computational costs.

2.3.1. Default control strategy

The default policy implemented in the test setup is an example of simple rule based control, focused on ensuring user comfort (Eq. 8):

$$u_t = \begin{cases} 1, & if\ T_s < T_{th} \\ 0, & if\ T_s \geq T_{th} \end{cases} \tag{8}$$

Here T_s is the temperature measured at the sensor and T_{th} is the default temperature threshold which forces a reheat cycle, usually set to 45 - 50°C. Because of stratification, the temperature gradient in the vessel ensures that water temperature at the outflow doesn't fall below 50°C usually. Statically setting this threshold lower has substantial negative repercussions for lost user comfort, as highlighted in the results section.

This rule based approach performs sub-optimally because no provision is made of the following facts in setting the value of u_t:

1. User DHW demand, i.e. $u_t = 1$, even during time periods where there is no foreseeable demand; this lowers energy efficiency because of two inter-related reasons. First, ambient heat loss is a nonlinear function of temperature difference between the water temperature and the ambient temperature. Therefore, losses can be reduced by forcing the storage vessel to operate at a lower average temperature. More subtly, it can also be reduced by forcing the reheat strategy to take into consideration periods of lower temperature. Second, the efficiency of the heat pump increases with higher temperature water at the inlet therefore the overall efficiency increases.
2. Nonlinear dynamics of the vessel caused by stratification effects in water [33], i.e. temperature at the top of the vessel is generally higher than at the mid-point which dictates the strategy; this effect becomes even more pronounced at the boundary where vessel response is highly nonlinear
3. Temperature dependent efficiency of heating mechanisms such as heat pumps, i.e. higher ambient temperature leads to more efficient heat pump operation (Eq. 9):

$$COP_h = \frac{T_{cold}}{T_{hot} - T_{cold}} \tag{9}$$

Where T_{cold} and T_{hot} are respectively the temperatures of the cold and hot heat reservoirs.

2.3.2. Heuristics for model based control

Having identified the obvious flaws in implementing the default control strategy, It can be replaced by a model based heuristic which optimizes energy efficiency while constrained on user comfort (Eq. 10):

$$\min(J)$$

$$\text{s.t.}$$

$$HW_t^{\pi} > 0, \ \forall \ k = \{0, 1, \dots T\} \tag{10}$$

Here HW_t^{π} is the amount of hot water in the vessel at time t following policy π, i.e. the amount of water the user would be able to draw above a predefined temperature threshold (in this case, 50°C). At every instant in time, the amount of hot water in the vessel under the proposed policy has to be strictly positive. In practice, enforcing this strict equality causes unnecessary reheat cycles, especially in high consumption houses where a rebound effect is observed, i.e. the energy consumed is sometimes even higher than in the default strategy because of frequent reheats triggered by predictable high user consumption. The following is a relaxation which was found to be more realistic (Eq. 11):

$$\min(J)$$

$$\text{s.t.}$$

$$HW_t^{\pi} \geq HW_t^{\pi_d}, \ \forall \ k = \{0, 1, \dots T\}, \ HW_t^{\pi_d} > 0 \tag{11}$$

Where $HW_t^{\pi_d}$ is the amount of hot water that would be available to the user if the default strategy were to be followed. In practice, finding the optimal u is a combinatorial optimization problem which can't be solved by complete enumeration. One heuristic that can find an approximately minimum solution is given as (Eq. 12):

$$u_t = \begin{cases} 1, \; if \; HW^{\pi}_{(v,t)} < \sum_{k=i}^{i+n} HW_{(p,k)} \;\&\; HW_t^{\pi_d} < HW^{\pi}_{(v,t)} \\ 0, \; otherwise \end{cases} \tag{12}$$

Here, the same terminology is used as before, to ensure that the heuristic does not use its additional information on user consumption patterns to improve comfort and rather ensures energy is minimized at comparable comfort levels. For houses with low consumption, the second constraint can be ignored and the heuristic reduces to (Eq. 13):

$$u_t = \begin{cases} 1, \; if \; HW^{\pi}_{(v,t)} < \sum_{k=i}^{i+n} HW_{(p,k)} \\ 0, \; otherwise \end{cases} \tag{13}$$

This heuristic, while ensuring just-in-time heating of the water vessel, ignores the ambient temperature. A second temperature peak-tracking heuristic constructs a policy by sampling points where the ambient temperature forms a local maxima. This heuristic is run for multiple values of the number of peaks chosen from the temperature time series and the best one is selected.

Both the heuristics are post-processed by implementing a stochastic search on the best policy found by the heuristic. In this case, we use simulated annealing to perform this intensification step, the neighbourhood search is limited to only moving the reheat cycles (i.e. where u_t = 1) forward or backward in time. This ensures a workable trade-off between computational speed and the quality of solutions found by active control (Fig. 3).

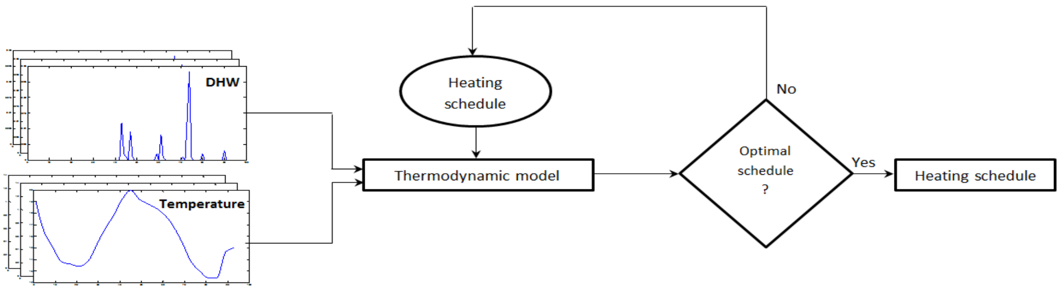

Figure 3: *Schematic of the algorithm for optimal DHW heating schedules*

2.3.3. Stochastic constructivist solutions: hybrid Ant-Colony Optimization

One problem with such constructivist heuristic solutions is that diversification is only performed as a post-processing step, i.e. in an intensified solution space. There is no diversification prior to the intensification step and this leads to very homogeneous solutions, which might perform continuously sub-optimally without any hope of correction. Since the solution space is combinatorial, complete enumeration is not possible.

One practical alternative is to treat the optimization problem itself as learning; in this way, regions in the solution space which yield promising solutions are identified over time. Further, this constructivist approach to sampling the solution space provides a more robust line of defence to the problem of non-stationarity. We propose a light-weight hybrid ant colony optimization (hACO) algorithm to perform this diversification.

The hACO uses an offline (diversification) and an online (intensification) step to learn the probability distribution of optimality in the solution space. In the following, we explain both:

2.3.3.1 Offline diversification

The offline phase is carried out using many different generic consumption profiles in simulations carried out over developed models of the storage vessel and heat pump. Since realistically there can be only a limited amount of DHW consumption profiles (i.e. DHW consumption per house can hardly exceed a few hundred litres per day), it stands to reason that the space of optimal policies is likewise limited. An alternative view of this step is forming communal knowledge or learning a prior over the solution space. This latter view is the one we take and treat the learning process as identifying hyper-parameters of the problem.

Completely enumerating each solution and then using this for learning makes for a combinatorial problem; to construct this distribution reliably would require an infeasible number of computations, so we construct different hyper-parameters and perform the learning process on this reduced space; these hyper-parameters identify features such as number of reheat cycles in a given time horizon, the distance between successive reheat cycles, the sub-sampling to be carried out etc. At the end of this offline step, a distribution emerges from which we can sample to construct solutions, instead of using heuristics.

It is important to note that solutions sampled from this distribution will not be optimal for every consumption profile. However, it is the subset of the combinatorial space which holds promising solutions. Essentially, this step has to identify the optimal trade-off between occupant comfort and energy consumption. On the one extreme lies never turning the heat pump on to minimize energy consumption, while on the other lies never turning it off to maximize user comfort. Somewhere in between is the optimal. Fig. 4 shows a stylized visualization of the knowledge of the ACO after the offline step.

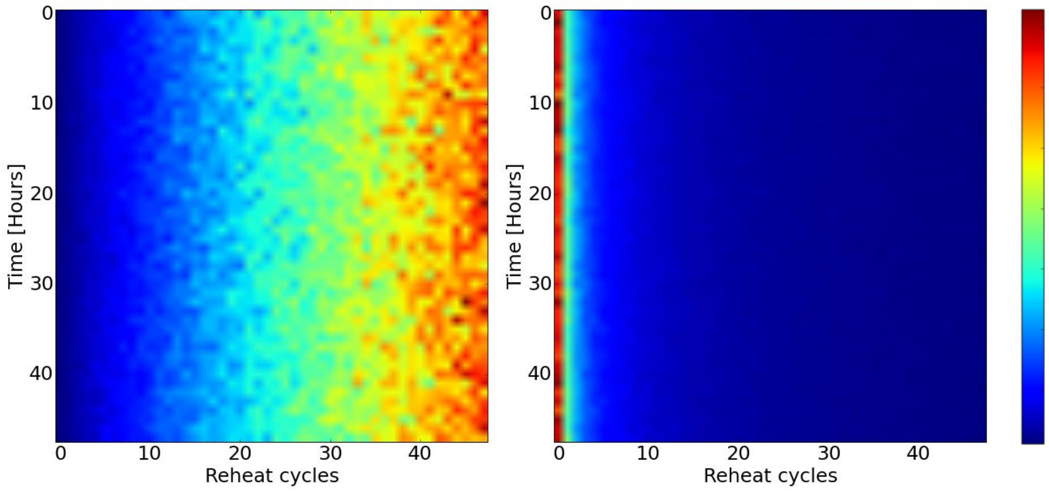

Figure 4: *Stylized visualization of (a) cost function (energy [kWh]) and (b) probability of lost user comfort; time horizon assumed to be 48 hours here*

2.3.3.2 Online intensification

There are two key differences between the offline and online operation. First, instead of using a uniform prior on the hyper-parameters as at the start of the offline step, here the prior is the distribution learnt after the offline phase. Second, in the online step, we use real consumption profiles for the household for which optimal control is to be performed. Thus, as more data becomes available for a particular house, the posterior distribution resembles the optimal distribution for that house more closely. Since the learnt distribution is non-parametric, multi-modal distributions don't pose any additional problems.

To form the posterior from the prior, both in the offline and online step, we use pheromone deposition as is commonly used in ACO literature. Another subtle distinction arises here between online and offline learning, in offline learning we don't use pheromone evaporation, while in online learning pheromone evaporation is implemented to ensure non-stationarity in occupant behaviour is properly handled.

2.3.3.3 Hybridization

Hybridization of the proposed ACO algorithm is implemented to speed-up the search process and prune unnecessary traversals. A branch and bound algorithm maintains the lower bound using the best solution found so far. Further, previously computed solutions can be used to identify the feasibility of subsequent solutions (based on user comfort), this helps the algorithm avoid simulating non-feasible solutions. Throughout all this, the algorithm maintains anytime behaviour, so the best policy identified so far is always available to the controller.

3. Results

In this section, main results of the prediction and optimization models proposed in the methodology section are presented. The results are split into two broad categories; model accuracy results and active control results. Energy efficiency is demonstrated in the active control sub-section through three different levels: (1) a training step which was carried out on simulations with gathered data assuming perfect information; (2) a validation step which was carried out using simulations but assuming real world conditions; and (3) a practical case study where the proposed methodology was implemented in a real house over 3.5 months.

3.1 Prediction results

3.1.1. Occupant model

The proposed SARIMA models provide reliable predictions for houses with regular consumption patterns. On the other hand, non-stationary, nonlinear and highly irregular consumption profiles are dealt with using the additional bias term. The regularity of the time series is evaluated by plotting its spectrogram using a windowed Short Time Fourier Transform (STFT) (Fig. 5).

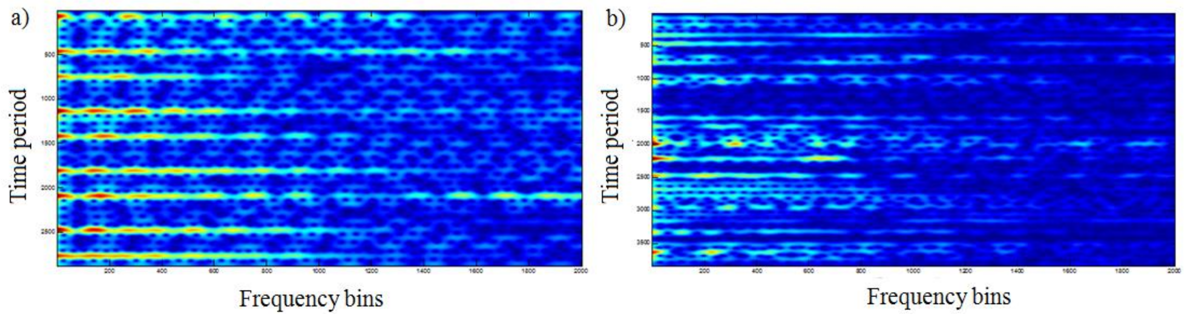

Figure 5: *Time-frequency decomposition of two DHW consumption profiles: (a) periodic consumption profile; (b) non-periodic consumption profile*

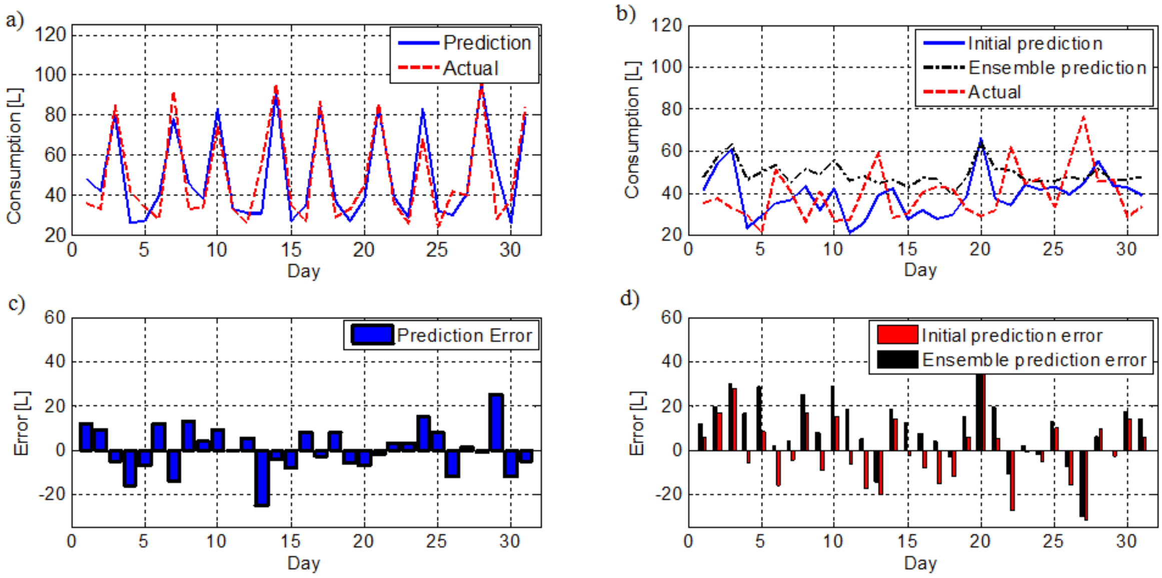

Figure 6: *Prediction results: (a) House with periodic consumption; (b) House with chaotic consumption; (c) Prediction error for periodic consumption; (d) Prediction error for chaotic consumption*

Depending on the estimate of the periodicity of the data, the predictor can decide to only use the SARIMA model or incorporate the additional bias term. Results for the prediction and prediction error for these two DHW consumption profiles are visualized in Fig. 6.

3.1.2. Cost function

We have used a polynomial regression model with regularization that predicts the cost in kWh i.e. the electricity consumption to reheat storage vessel given current state and ambient temperature. This is primarily to model the initial nonlinearity in the system response, i.e. a linear model always predicts that the storage vessel would require a substantial amount of electricity equal to the bias term in the fit model, even immediately after the previous reheat cycle. A higher order model prevents this and, in general, performs reasonably well on both the training and validation test sets. Fig.7 plots predicted energy consumption against observations and also the distribution of prediction errors.

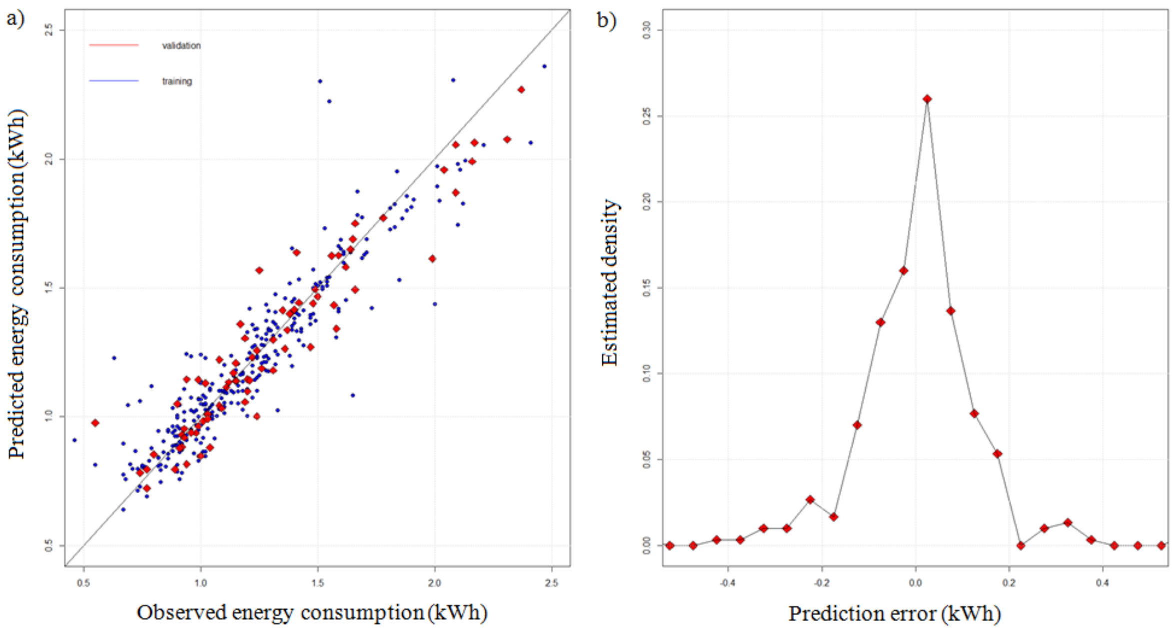

Figure 7: *Performance of quadratic model to predict reward function a) Observed vs. predicted electricity consumption with line of perfect fit, b) Distribution of errors*

3.2 Optimization results

3.2.1. Energy efficiency

3.2.1.1. Training performance

In the training phase, the optimizer is assumed to have perfect information about future user demand; furthermore, errors in electricity consumption and storage vessel state are discarded. Active control's performance is evaluated by testing on consumption profiles that the optimizers haven't seen yet. This has no effect on policies provided by the default controller as well as model-based control, however for the proposed hACO, it serves as a first benchmark for validation purposes regarding whether the pheromone trail deposited by the ants was successful in identifying good regions of the solution space. Figure 8 presents the results for running different control strategies; in each strategy, user comfort is constrained to be no worse than the default policy.

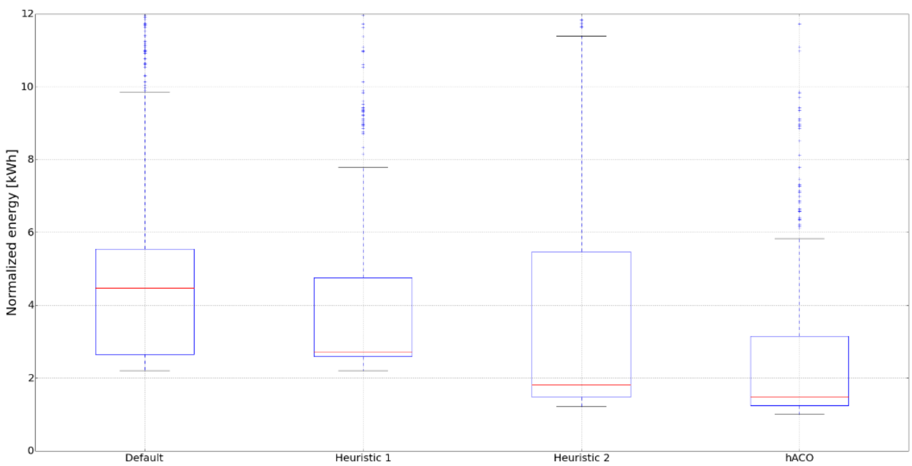

Figure 8: *Aggregated energy efficiency Performance*

The two heuristics are as defined previously in section 2. Overall energy savings for these two heuristics and the ACO optimizer are 24, 27 and 36% respectively, when compared with the default strategy. This is clearly seen in figure 4 where the ant colony optimizer clearly combines the best features of both heuristics in the sense that both the expected energy consumption and the variance about it is minimized. By the imposition of hard constraints on feasibility, user comfort is ensured as well. This is further visualized in figure 9 where we see the estimated energy consumption of running the algorithms on 50 different demand patterns for two days. As highlighted in the boxplot previously, the energy consumption with ant colony optimization usually succeeds in finding a better policy than that found by vanilla heuristics with search.

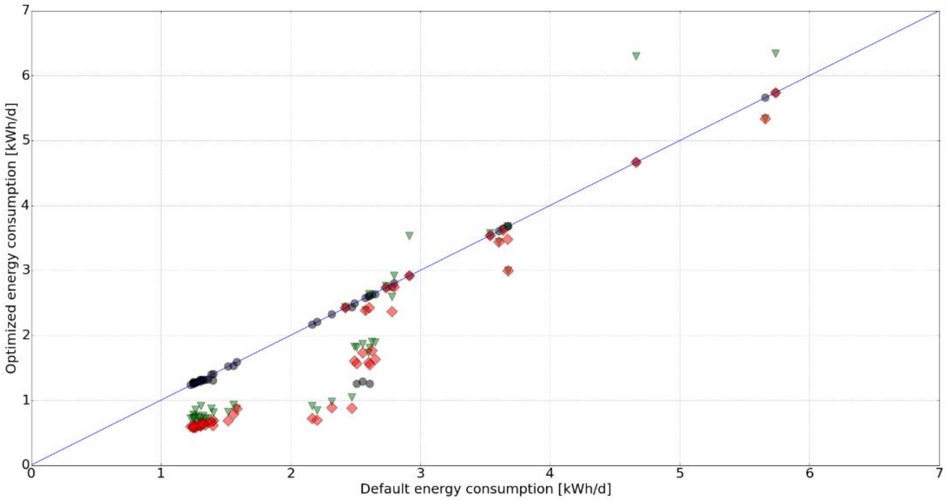

Figure 9: *Episodic energy efficiency performance*

3.2.1.2. Validation performance

In contrast to the training step which is meant to validate the behaviour of ACO in ideal conditions, we now turn our attention to the real case where such knowledge is not available in advance in the online step. This means that consumption profiles for the user are predicted first and then control actions are taken. Furthermore, the optimizer performs control in the simulated environment as part of a receding horizon framework for an entire month. Figure 10 illustrates these results for weekly draws over the month for 2 houses:

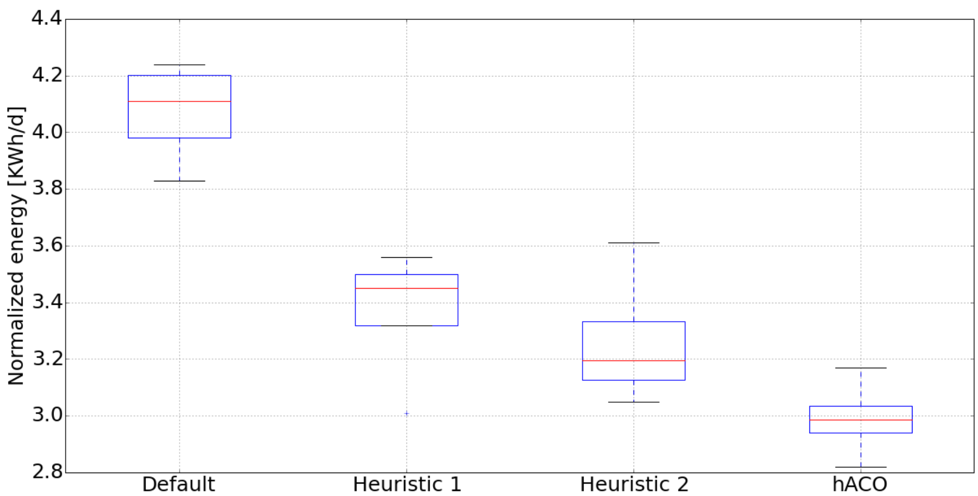

Figure 10: *Energy efficiency gains in test environment*

Expected reduction in energy consumption is 17, 20 and 27% respectively compared to the default case (with significant spread, explained for by the individual occupant behaviour). These gains are lower than what was seen for the validation test and can be explained primarily by the uncertainty arising because of lack of perfect information about user demand. A more accurate prediction or running stochastic optimization can help further reduce this gap between theoretical and practical efficiency gains.

3.2.1.3. Real-world performance

Finally, we present the results of running active control on a real house. The house chosen for optimal control is a low consumption house (about 60 litres/ day of DHW consumption). To manage complexity and limit the risk of lost user comfort, model-based heuristic control to evaluate savings was implemented in the first phase after an initial monitoring period. The monitoring period lasted from 15 September, 2015 until end of November, 2015. From the start of December to mid-March, 2016, active control was applied. This is visualized as the two regions in fig. 11.

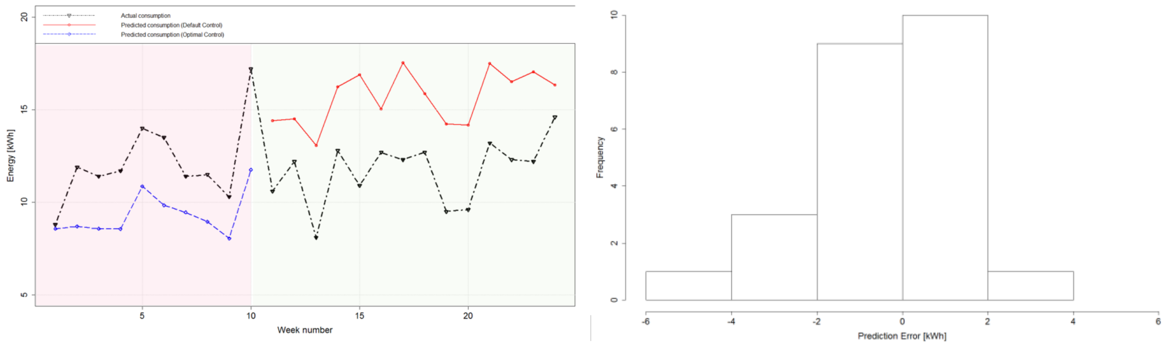

Figure 11*: (a) Comparison of energy consumption with simulated consumption – red region signifies default control strategy while green region represents savings with optimal control; (b) error between predicted and observed*

During the time period when active control was implemented, energy consumption was reduced by approximately 27%; in absolute terms this accounted to about 61 kWh saved in 3.5 months or 210 kWh/a by extrapolation. In the next phase of implementation, the hACO algorithm will be rolled out to this and other houses, potentially further increasing energy savings.

Fig. shows the error between the predicted and actual energy consumed to provide DHW given a certain vessel state. The error is zero-mean with fairly low variance. The variance, which is higher than the cross-validation error, can be explained by the low ambient temperatures in winter for the test period. During the initial training phase, the model did not see such data; despite this, the model exhibits fairly low bias. As more data became available, model parameters were updated so performance is expected to improve further over time.

3.2.2. User comfort

Fig.12a illustrates the results of the optimization algorithm applied to seven different houses; it highlights that by applying the proposed control strategy a reduction of electricity consumption can be seen. Substantial energy savings from the default behavior are apparent for the daily energy consumption. At the same time, it is imperative to ensure that improved energy efficiency does not come at the cost of the comfort people are accustomed to. In this regard, the drop in consumption temperature is foreseen and is a necessary part of the optimization process. However, this does not affect user comfort, since at no point is the water outflow temperature allowed to fall below the threshold of 50°C. Fig.12b lends further credibility to this hypothesis where many reheat episodes are analyzed for a single house. Using the vessel model presented earlier, we were able to glean the behavior of the default vs. optimal control strategies (by visualizing the temperature distribution in the vessel just before the reheat signal). Optimal control is forcing the heat pump to postpone heating such that less hot water is available at the time of the reheat cycle. This has to balance safeguarding user comfort while minimizing electricity consumption.

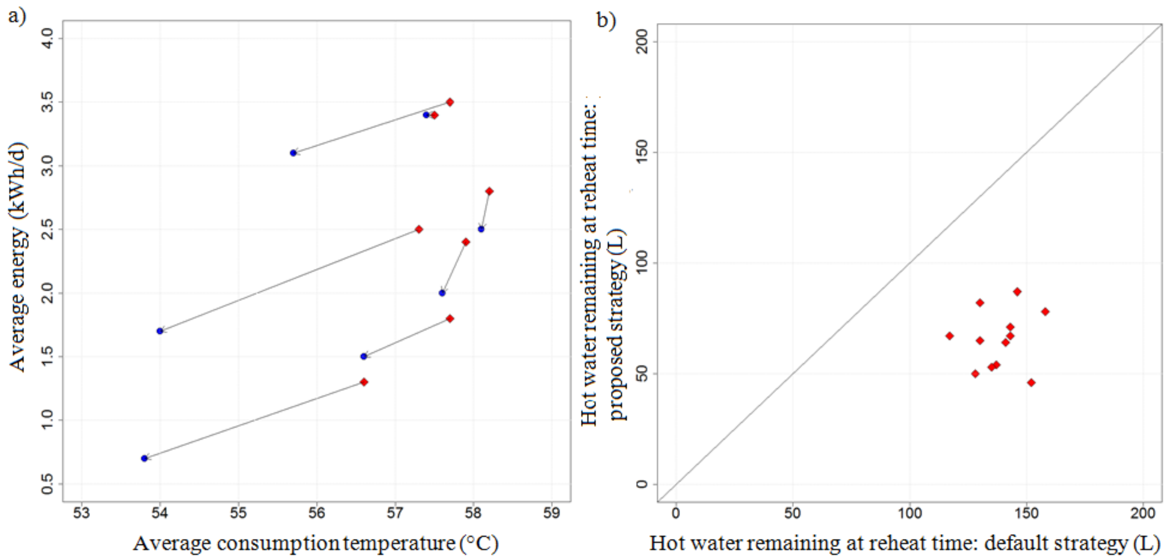

Figure 12: *Effect of optimization on user comfort: a) Shift in consumption temperature vs. electricity consumption after optimization as visualized for 7 houses; b) Reduction in remaining hot water in the vessel at reheat time as visualized for 1 house*

3.3 Target temperature sensitivity results

While so far the focus of the study has been to search for optimal DHW operational schedules, it is worthwhile to investigate whether the target temperature of reheat cycles can be changed to further reduce electricity consumption. This relationship depends on multiple factors:

1. Lower ambient losses due to lower overall energy content
2. The heat pump has a higher operating COP because of lower average intake water temperature

On the flipside, by lowering the overall energy content in the vessel, the probability of reducing user comfort becomes higher. In fact, experiments, where the target temperature was lowered disregarding user consumption, were reported to backfire with occupants complaining about lost comfort.

The solution is to determine a target temperature for each house at each optimization time step. Considering the high computational cost of this operation, a useful practical compromise is to refresh the target temperature once every fortnight. In effect, determining this set point follows a pattern not dissimilar to a sensitivity analysis where multiple values of target temperature are evaluated retrospectively to see the best compromise between energy consumption and user comfort. The set point that achieves this balance is then used in conjunction with the simulated annealing algorithm. This is visualized in Figure 13.

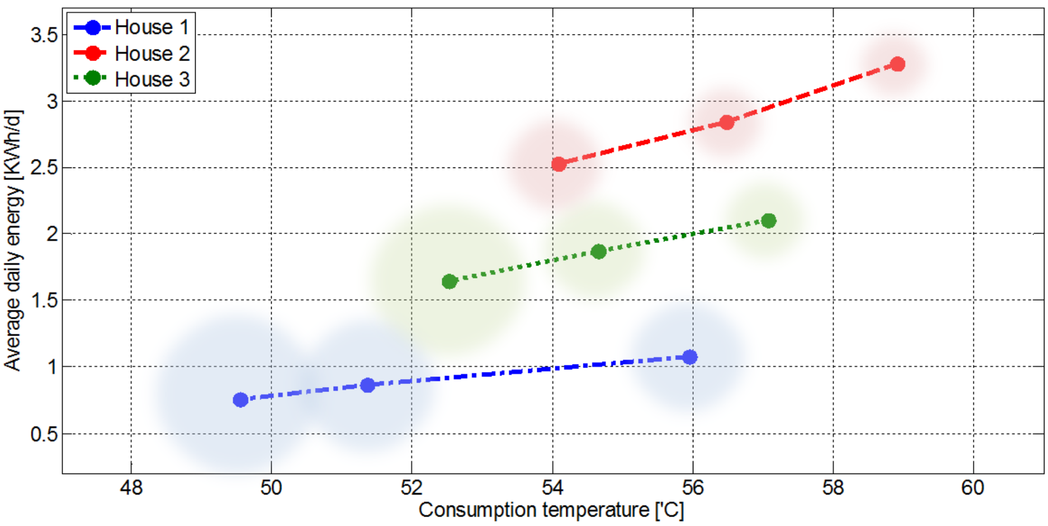

Figure 13: *Sensitivity analysis with target temperature variation*

4. Discussion

The primary objective of this research project was to investigate further improvements in the overall energy efficiency of highly efficient net-zero energy buildings by performing active control for DHW production. More concretely, emphasis was placed on reducing the electricity consumed by considering data-driven optimizations based on real occupant behaviour and learnt models for the heating mechanism. Despite numerous technical challenges, simulations show that such savings are indeed possible in practice.

The research also confirms some intuitive hypothesis presented before in this paper. The energy consumed in these highly insulated buildings over the winter period for spatial heating was higher than that consumed for DHW, but the difference was less pronounced than in low efficiency buildings (Fig. 14).

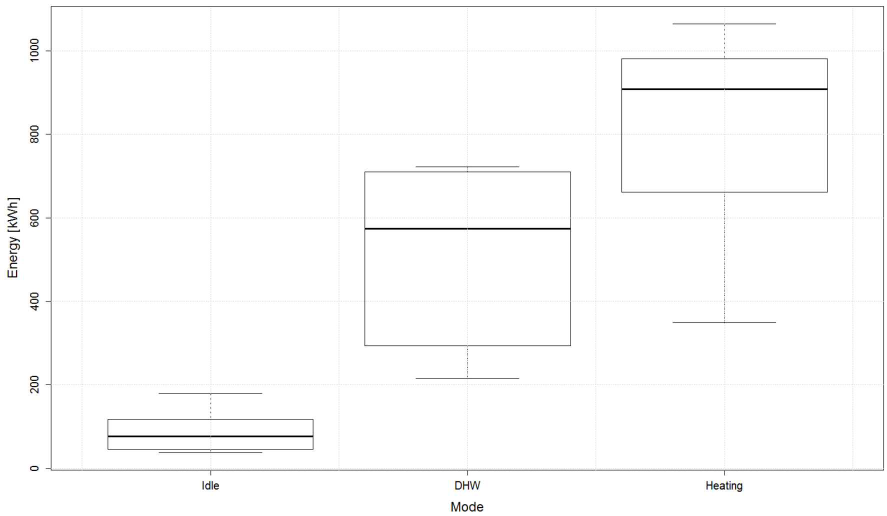

Figure 14: *Distribution of energy consumed in different operating modes for six houses (idle, DHW and spatial heating)*

While hardly surprising, this result provides evidence for the hypothesis that as façade efficiency of a building increases, the energy consumed for DHW increases in relative terms. This brings us to a second, more subtle point. The optimization is not unconditional, but is subordinate to the occupant behaviour. The energy consumption for DHW of an individual household is a function of the amount of hot water it consumes and the ambient losses. Any gains in energy efficiency likewise follow a trend where greater daily water consumption lessens the impact of heat losses to the ambient and, therefore, reduces the flexibility to optimize the heating schedule (because of user comfort constraints). This effect is visualized in fig. 15.

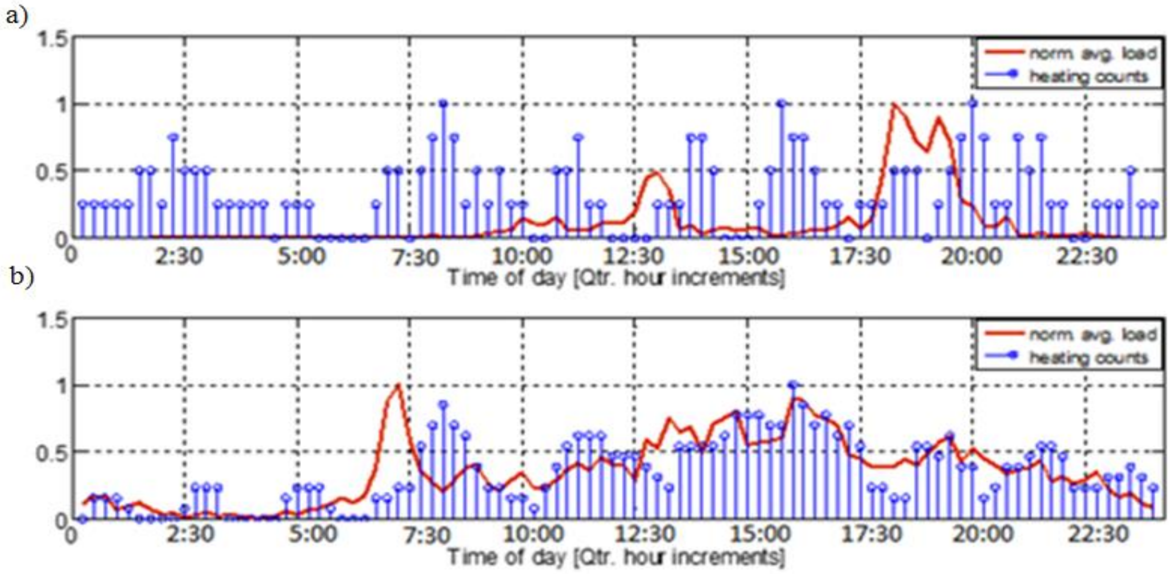

Figure 15: *Heating regimes in default behavior: a) Loss driven heating for a house with low daily water consumption, b) Consumption driven heating for a house with high daily water consumption*

This distinction between loss driven and consumption driven heating regimes has important implications for which houses are best suited for the optimization algorithm and which ones would pose a greater risk leading to lost user comfort.

Loss of user comfort and privacy concerns are the two greatest risks facing widespread acceptance of such intelligent control. User comfort is ensured by developing a sophisticated prediction framework which essentially penalizes under-prediction of water consumption much higher. At the same time, if the prediction policy becomes too conservative because of consumption predictions which are too high, control is switched back to the default strategy. The second risk pertains to data privacy and, as a potential safeguard, all the algorithms developed in this research have been kept as lightweight as possible. The anytime nature of the active control formulation allows local deployment of these algorithms without the need for communication to a central server or sophisticated hardware at the user's premises.

Furthermore, the findings also corroborate the efficacy of using heat pump based systems to introduce dynamic flexibility; this kind of system can thereby help in adjusting the load on the electric grid. The gain in energy efficiency is essentially the flexibility in heat pump operation, which can be leveraged as demand response towards the electric grid without affecting user comfort. This is visualized in Fig. 16a as upward (positive flexibility) and downward (negative flexibility) regulation of electric energy. The flexibility is plotted as kWh, which simply implies how much energy can be further pumped into the vessel for upward regulation. On the other hand, downward regulation is activated only when the heat pump is reheating the storage vessel and is the amount of energy that still needs to be consumed to completely reheat the storage vessel. It is important to note here that in plotting these figures, we are not considering the different power profiles depending on the storage vessel state, *x*.

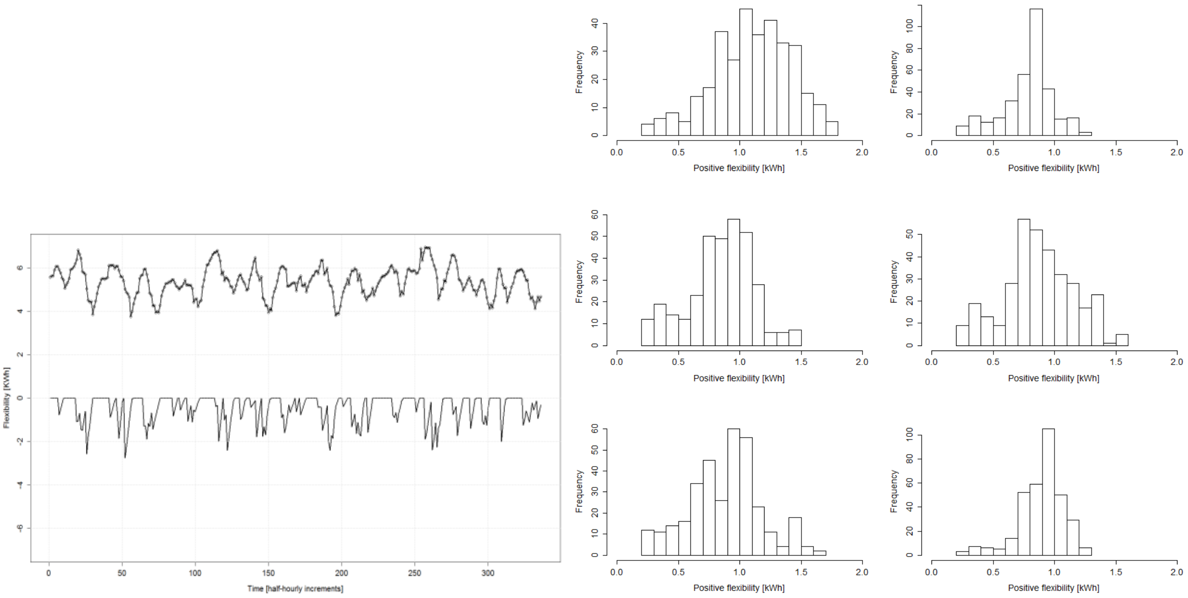

Figure 16: *(a) Demand Response potential, plotted as a time series; (b) Histograms for individual house's positive flexibility (upward regulation)*

The limited number of houses under consideration, six in this case, means that the upward regulation is much higher than downward regulation. As more devices and houses come online, this is projected to increase proportionally as well. Fig. 16b shows the distribution of each house's individual flexibility. It is evident from even this limited example that there are significant differences in both the mean and variance of offered flexibility. As already indicated, the main driver for this is again the occupant behaviour. Leveraging this information in a global optimization problem allows for practical residential ADSM, thereby aligning heating policies in such a way as to provide relief to the stressed grid or take advantage of lower electricity market prices.

5. Conclusions

Detailed simulation results presented in this study show that, on average, 20% savings in the energy consumed for DHW is achievable with model based heuristic control. By making the optimization process data-driven as well, simulations show savings up to 27% on average. The variance around these savings is primarily explained by the different occupant behaviour (higher consumption somewhat counter-intuitively imply lower relative savings). Results from these simulations are borne out by active control performed in a house over 3.5 months, which resulted in energy savings of approximately 61 kWh, or 27% of the energy consumed for DHW production. This is in line with our expectations since the house had a lower than average water consumption. Active control is constrained on the condition that user comfort should be no worse than in the default control strategy. We postulate that wide-spread implementation of this control has the potential to:

1. Help highly efficient (or nearly-zero energy) buildings conform to their design specifications
2. In case of already net-zero energy builds, rebranding as positive energy buildings or reducing the amount of on-site energy production by solar PVs - which can help reduce investment costs and is thus a direct financial reward as well

As human society transitions towards sustainability, discussion on smart buildings and grids is poised to dominate the political and scientific landscape for many coming years. This project is a practical step in supporting this transition in the ongoing evolution of highly efficient residential buildings.

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